Analysis of Electrocardiographic (ECG) Signals

OBSS - 1. Assignment

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Abstract

This article aims to enhance the QRS complex detection algorithm proposed by HC Chen and SW Chen in their work, "A Moving Average based Filtering System with its Application to Real-time QRS Detection." The filtering stage is improved by introducing a more sophisticated signal transformation. The decision-making stage is enhanced by refining the adaptive threshold method and incorporating a minimum distance constraint between heart beats. The algorithm is tested on the Long-Term ST Database, yielding a sensitivity of 99.66% and a positive predictive value of 99.81%. The results surpass the original article, demonstrating the effectiveness of the proposed improvements. Further refinement of parameters and algorithmic components is discussed for future work.

1 Introduction

The analysis of Electrocardiographic (ECG) signals plays a pivotal role in modern healthcare for the assessment of cardiac health and the early detection of abnormalities. In the pursuit of advancing QRS complex detection, this article builds upon the foundation laid by HC Chen and SW Chen in their article, "A Moving Average based Filtering System with its Application to Real-time QRS Detection" [1]. Our objective is to enhance the algorithm's effectiveness through a comprehensive revision of both the filtering and decision-making stages.

In this paper, we present a reevaluation of the original algorithm, introducing substantial improvements to the filtering stage by enhancing the signal transformation process, incorporating multi-lead analysis and a subsequent smoothing step to refine the output. The decision-making stage undergoes significant refinement, with an adapted adaptive threshold mechanism and an added minimum distance constraint between successive heartbeats.

2 Methodology

The initial article adopts a straightforward structure, initiating the filtering stage by employing a moving-average filter (Linear High-Pass Filtering) to process the signal, followed by squaring the resultant signal (Non-Linear Low-Pass Filtering). Subsequently, the process advances to the decision-making stage, wherein an adaptive threshold method is applied to ascertain whether the signal's increment signifies the presence of a QRS complex. The subsequent subsections elaborate on enhancements made within each stage.

2.1 Filtering Stage

We enhance the reliability of the filtered signal by introducing more sophisticated signal transformations. The entire filtering process is encapsulated by Equation 1. Instead of singularly considering one filtered signal, we aggregate the approximations of the first derivative (Equation 2) and second derivative (Equation 3) for each available lead [4]. The resulting sum is squared, amplifying the distinction between noise at the bottom and peaks representing the QRS complex. Preceding the decision-making stage, we further refine the signal with a 24-point moving average (Equation 4).

The broad nature of the smoothing filter accommodates potential double peaks.

$$d[n] = G((\sum_{i=1}^{N}(|H_1(x_i[n])| + |H_2(x_i[n])|))^2) \quad (1)$$

$$H_1(z) = (1 - z^{-6}) \cdot \frac{1 - z^{-6}}{1 - z^{-1}} \quad (2)$$

$$H_2(z) = (1 - z^{-6})^2 \cdot \frac{1 - z^{-6}}{1 - z^{-1}} \quad (3)$$

$$G(z) = \frac{1 - z^{-24}}{1 - z^{-1}} \quad (4)$$

Figure 1 illustrates the comparison between the original signal (from one of the leads) and the output after the filtering stage.

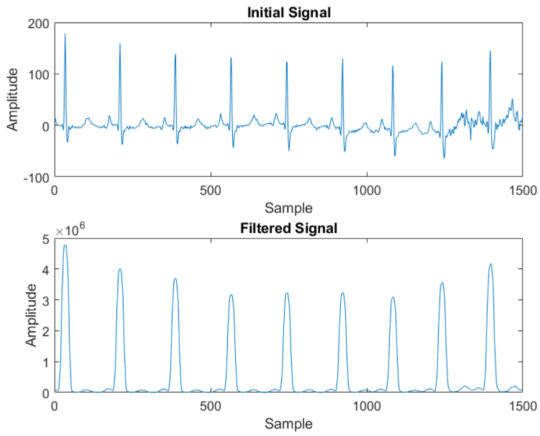

Figure 1: A visual comparison of the raw and filtered signals.

2.2 Decision-making Stage

The adaptive threshold method, as expressed in Equation 5, aligns with the formula used in the original article. However, the real-time peak detection approach may differ from the original implementation, which lacked specific details regarding peak location during simulated real-time detection.

In our methodology, the initial threshold, $Threshold_1$, is derived from the local maximum of the first 300 samples in the record: $Threshold_1 = PEAK_1 \cdot 0.85$. Subsequently, we traverse the signal one sample at a time, simulating a real-time system without sliding windows. As we cross the threshold, we commence recording the indices, halting when descending below the threshold. The value at the central index of the saved indexes, although not necessarily a local maximum, is designated as the peak. The adaptive threshold is then recalculated based on this peak.

$$Threshold = \alpha \cdot \gamma \cdot PEAK \cdot (1 - \alpha) \cdot Threshold \quad (5)$$

To refine peak detection, we introduce a minimum allowable sample distance between two consecutive heartbeats [3]. This inclusion substantially mitigates false detections, consequently elevating the positive predictive value.

3 Results

The algorithm underwent thorough testing and validation using the complete Long-Term ST Database (LTST DB) [2]. The achieved results demonstrate a commendable sensitivity of **99.66%** and a robust positive predictive value of **99.81%**. Both gross and average values concurred.

Optimization of results was accomplished through meticulous parameter tuning in the decision-making stage. The optimal parameters utilized were $\alpha = 0.05$, $\gamma = 0.25$, $Threshold_1 = 0.85 \cdot PEAK_1$, and a minimum distance of 70 samples between two neighboring heartbeats.

Notably, the attained results slightly outperformed those reported in the original paper. This improvement is attributed to the heightened complexity of our filtering approach and the introduction of supplementary parameters in the decision-making stage. Despite this overall success, record 's30781' exhibited a sensitivity of approximately 85%, representing the algorithm's least favorable performance. Further analysis and refinement are warranted to address specific challenges posed by this particular record.

4 Discussion

The testing phase did not encompass adjustments to the filter size, a factor that holds potential for further enhancement of results. Additionally, the decision-making stage requires continued refinement for optimal performance.

The record exhibiting the least favorable performance, with a sensitivity of around 85%, highlights a noteworthy area for improvement. This sensitivity value signifies that approximately 15% of heartbeats went undetected. The discrepancy suggests a potential issue within the implementation of the adaptive threshold. Addressing and refining this aspect is imperative for achieving a more comprehensive and accurate detection of cardiac events.

References

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